2-Layer Classifier for Facial Recognition

Xiaolu Yang and Junyi Zhao

***Abstract*—This paper presents a method using a compound classifier which exploits both Gabor features and Fourier features extracted from input images. Gabor wavelet is used to capture facial relevance characters, i.e. Gabor features, in different scales and directions. Given the high-dimension of Gabor features, we employ PCA method to refine them. Then, Fourier features are exploited by applying the Discrete Fourier transform to images and then retaining the low-frequency coefficients, which contain the facial contour information. Thus, 2 classifiers are obtained: one based on Gabor feature, the other based on Fourier feature. Finally, the 2 classifiers will be integrated together to form a final classifier. We evaluate this method using ORL face database. Experimental results illustrate the performance of this method compared with PCA and FLDA.**

***Index Terms*—2-layer classifier, gabor feature, fourier features, PCA.**

I. INTRODUCTION

Facial recognition has always been a challenging, focused field. To make full use of image information is a hot spot during recognition, especially when having only limited number of images at hand. Gabor wavelet is introduced to image analysis because of its biological relevance and computational properties [1]. Information extracted by Gabor wavelet derives desirable features characterized by orientation selectivity, spatial frequency and locality. In reference [2], author integrates the Gabor wavelet representation with kernel PCA method for facial recognition; in [3], Gabor wavelet has been combined with PCA-FLD for classification. It is worth investigating Gabor wavelet in other combination. Additionally, Fourier transform can be an outstanding method that transforms image data into frequency domain; the transform makes hidden characteristics to emerge. Fourier method has been widely used in recognition, such as tire imprint recognition [4], face detection algorithm [5]. We can obtain important features of original image — main organ characters — from these frequency data. In this paper, we present a method combining Gabor wavelet and Fourier transform together.

II. LAYER CLASSIFIER CONSTRUCTION

Obviously, both holistic and detailed features embedded in the face image are of critical significance to our recognition. The former covers the whole facial configuration and organ contour depicted through illumination in certain direction. And the latter reflects variations in most regions and the relevance among them in general. In terms of recognition, each one of these two features has its advantage over the other; they are complementary to some extent. Thus, appropriate combination of these two can benefit our recognition goals.

As mentioned above, we will construct a 2-layer classifier in which each layer corresponds to one kind of feature. Firstly, we apply Gabor wavelet to the whole input image, collect Gabor feature in different metrics; then refine these features to form the 1[nd] layer classifier. Secondly, we use Discrete Fourier Transform (DFT) to import image data into frequency domain, then extract low-frequency information and construct the 2[st] layer classifier. Finally, we inosculate 2 classifiers into a final one by assigning each one a proper weight.

A. Gabor Feature Extraction

Gabor wavelet is a complex exponential function modulated by a Gaussian function, which has been used to model the receptive field of the orientation-selective cells. Its concerning about biological relevance while extracting features makes itself a popular method in recognition field. The Gabor kernel can be defined as follows:

$$\psi_{u,v}(z) = \frac{\|k_{u,v}\|^2}{\sigma^2} e^{-\frac{\|k_{u,v}\|^2 \|z\|^2}{2\sigma^2}} \left[e^{ik_{u,v}z} - e^{-\frac{\sigma^2}{2}} \right]$$

Here, $z = (x, y)$, $\|\cdot\|$ is the norm operator, $k_{u,v} = k_v e^{i\phi_u}$ ($k_{u,v}$ is the wave vector, $k_v = k_{\max} / f^{v}$, $\phi_u = \pi u / 8$, and $k_{\max}$ is the maximum frequency, *f* is the spacing factor between kernels in the frequency domain), *u* and *v* define the orientation, scale of Gabor kernel.

Gabor features of image are extracted by convolving the whole image with Gabor kernel. In order to make full use of the texture features within an image, we choose different sets of parameters to fetch facial texture in 4 scales and 6 orientations ($u \in \{0, \cdots, 5\}$, $v \in \{0, \cdots, 3\}$) as illustrated in Fig. 1.

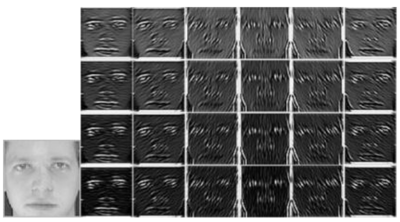

Fig. 1. An original image, and its Gabor representations with 4 scales and 6 orientations..

Given an image matrix of dimension W×H, we convolve all the Gabor filters (4 scales and 6 orientations) with this

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matrix, so we get 24 Gabor feature matrices of each image. Then we concatenate all the W×H Gabor feature matrices in column direction and it yields a 24WH×1 column vector. Obviously, Gabor data that we obtained is of prohibitive dimensionality, we need to cope with this problem. Principal Component Analysis (PCA) is the most commonly used method for dimensionality reduction by retaining eigenvectors that contribute most to the variance, and abandoning ones corresponding to minor eigenvalue. Assuming there are n training images, the Gabor features matrix G will be 24WH×n.

Mean vector of all training images: $X = (1/n)\sum_{i=0}^{n} g_i$

(g_i is the column vector of G)

Calculating difference matrix *w*: $w_i = g_i - X$ *(i=1, ... , N;* w_i is the column vector of *w)*

If we solve eigenvectors by first calculating $C = ww^T$ then *C*'s eigenvector, there could be huge amount of computation due to *C*'s high dimensionality. According to linear algebra theory and reference [6], we have an alternative way to obtain eigenvectors: computing covariance matrix C by multiplying *w*'s transposition with *w* itself, i.e. $C = w^T w$, then calculating *C*'s eigenvectors. Owing to *w*'s row number (i.e. number of pixels) is always larger than its column number (size of training set) according to previous processing way, the alternative way contributes a lot to reducing computational complexity. Finally, we extract each eigenvector whose counterpart eigenvalue is greater than the average of all eigenvalues to form an eigenface.

B. Fourier Feature Extraction

As we known, different frequency bands play distinct roles in the image representation. From the standpoint of frequency analysis, facial configuration features should mainly correspond to the lower frequencies. To be concrete, the magnitude of image frequency should indicate the speed of change in color. In other words, low-frequency can reflect the main organ characters (E.g. forehead, cheek.) as the color of these facial parts do not always change abruptly. Moreover, these parts compose the main area of face and can reflect facial contour. In Fig.2, (a) is the original image, (b) is the image constructed with reverse transform using low-frequency part of original image. Fig.2 (b) illustrates the reason why adopting low-frequency in our 2nd layer classifier.

(a) Original images

(b) Images reconstructed by using low-frequency Fourier features.

Fig. 2. Images' reconstruction comparison.

In this paper, we utilize Discrete Fourier Transform (DFT) to extract low-frequency information. In most general situation a 2 dimensional DFT takes a complex array. As for image processing, each value in the array represents a pixel, therefore the real part is the pixel value and the imaginary part is zero. 2-D Fourier transform simply involves a number of 1 dimensional Fourier transforms. More precisely, a 2-D transform is achieved by first transforming each row, replacing each row with its transform and then transforming each column, replacing each column with its transform. Thus a 2D transform of a M by N image requires M+N 1D transforms.

$$F(u,v) = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)e^{-j2\pi(ux/M+vy/N)} \quad (u, x=0,1,2,\cdots,M-1;\ v, y=0,1,2,\cdots,N-1)$$

Here *f(x, y)* is the input image of dimension *M×N*; *(x, y)* are the pixel coordinates in the image and *(u, v)* are coordinates in the "transformed image *F (u, v)*.

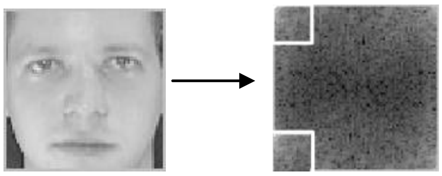

Fig. 3. Transform original image into frequency domain, then extract low-frequency Fourier feature in certain areas.

Using Fourier transform, we obtain the frequency statistics of the whole image in the form of complex array. Then the low-frequency features illustrated by 2 white squares (8×8) in Fig.3 will be filtered as required and reshaped into a 1-D column vector for further use. Since a complex value has a real and an imaginary part, the 1-D vector we get will have 8*8*2*2=256 rows. Selecting features pointedly in this way not only produces features useful to us, but also reduces computational cost by confining computation within certain patches. Finally, we have a matrix in which each column is the 1-D vector of low-frequency values from individual image. In this stage, we also apply PCA to this matrix to construct low-frequency eigenface.

C. 2-Layer classifier

After two procedures above, we will have two classifiers (i.e. eigenfaces): one based Gabor feature— C_G, the other from Fourier low-frequency— C_F, which play different roles in our recognition and may have distinct contributions to it. Gabor is focusing on facial textures, while capture facial contour is taken care of by Fourier transform. Hence, classifier trained on different feature set of discriminant information should have large diversity in recognition. Considering this, these 2 classifiers can be combined together to enhance recognition performance in the following way: $C = wC_G + (1-w)C_F$, *(0<w<1)*. Here, *w* is the weight of C_G determined by C_G's contribution to *C*, the impact of different weights for the classifier combination will be shown in experiment. And combined classifier is superior to the single classifier in a way.

III. Experiments and Conclusion

In our experiment, we utilize ORL (Oracle Research Library) face database. It is a library widely used in recognition with 40 subjects, 10 images of each subject. These images are taken at different times under different illumination with various expressions. All the images are taken against a dark homogeneous background and the subjects are in up-right, frontal position (with tolerance for some side movement). Actually, we trim images from 112×92 to 72×72 by retaining major part of face. Due to facial variations invited by illumination and background, etc, recognition will be influenced by noise from image itself. Thus, PCA has been applied in each stage of classifier construction to refine facial features for good performance. The experiment will try different combination of these 2 classifiers by assigning weight *w* to C_G, 1-*w* to C_F (*w* ranges from 0.05 to 0.9), and then compare the performance with FLDA, PCA methods.

By choosing 2, 3, 4, 5, 6 images respectively from each subject, size of our training sets can be 80, 120, 160, 200, and 240. We calculate Euclidean distance to classify images in our method and in two other methods applying FLDA and PCA separately. And in this comparison experiment, we assign 0.5 to weight *w* assuming the Gabor and Fourier feature having same contribution to final classifier. Fig.4 shows the comparison. When training set is of small-scale, performance of 2-layer classifier method remains steady; as the scale becomes larger, our method shows it potential: the slope of accuracy curve is obviously higher than the other two methods.

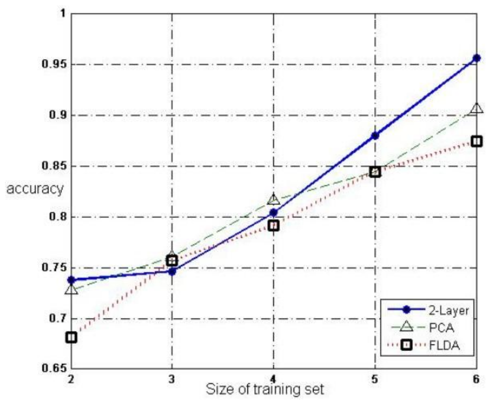

Fig. 4. Comparison of recognition accuracy among 2-Layer classifier, FLDA and PCA method.

Fig.5 demonstrates the impact of weight *w* (weight of C_G) to 2-layer classifier method; we assign *w* alternately from 0.05 to 0.9 with step-size of 0.05 and size of training set is 200 (selecting 5 images per subject). The holistic recognition rate declines when the weight of Gabor Feature increases. And the Fourier feature contributes a lot compared with the Gabor wavelet feature. So low-frequency Fourier feature is the dominant factor in our method.

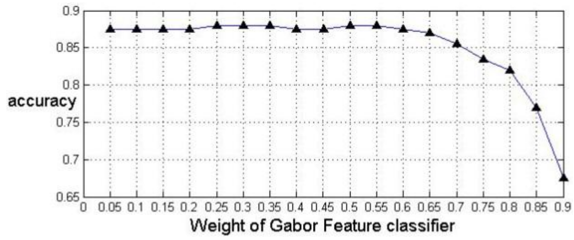

Fig. 5. Impact imposed by weight by assigning Gabor classifier weight w ranging from 0.05 to 0.9.

Major organ features reflected by low-frequency information plays a critical role in recognition because they depict shape of facial organs, and variation of illumination can be seized in these areas. It can be concluded that 2-layer classifier method runs well when compared with applying PCA or FLDA alone in a way. But there are some deficiencies: the Gabor wavelet we apply to fully utilize detailed texture feature does not live up to our expectation to some extent. Gabor wavelet to extract texture is worth carefully examined to improve the classifier. And, a better combination of classifier can be another way for further exploitation.

Acknowledgements

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